A COMPARATIVE ANALYSIS BETWEEN IMAGE SEGMENTATION ARCHITECTURES: U-NET AND U-NET++

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Introduction

The recent trend in technological developments has opened the door to many innovations, especially in medical imaging. I will be making a distinction between U-Net and U-Net ++ in this post. At the University of Freiburg, in the Computer Science Department, U-Net, which is a convolutionary neural network, was developed for biomedical image segmentation [1]. The network consists of completely convolutionary networks. By using dense block and convolution layers between the encoder and decoder, U-Net++ aims to enhance segmentation precision. Segmentation accuracy is very important for medical images because segmentation errors would yield unreliable results; thus, will not be accepted for clinical settings [2, 3].

Background

Similar work was conducted on a neural network before U-Net to segment neural membranes involving image segmentation. The network type uses a sliding-window to forecast for each pixel by providing as an input a local segment (patch) in the provided pixel [3]. This related work had the following limitations: a) scanning each patch and a lot of redundancy due to overlap, it is very slow b) It was not possible to measure the size of the sliding window that affects localization accuracy. Deep convolutionary networks have had an immense advance in the state of the art in the last decade [4, 5].

Knowing the fact that convolutional networks have existed for quite some time [6], their success was restricted due to the magnitude of the availability of training sets and the extent of the access networks. The revolution by Krizhevsky et al. [7] was due to the supervised training of a great network with 8 layers and millions of limits on the ImageNet dataset with a lot of training tomography and other images [8]. Segmentation errors in medical images also occur that require greater accuracy than in natural images, errors in medical images can result in a poor user understanding in a clinical setting. The proposed architecture is efficient, according to this review, yielding significant performance gain over U-Net and wide U-Net. U-Net++ has three additions to the original U-Net, which includes: a) Redesigned skip pathways b) Dense skip connections and c) Deep supervision.

Methodology

Four different medical imaging datasets for training purposes, covering different lesions/organs from a variety of medical imaging Architectures which shows the matching output. The input images and their equivalent segmentation maps are used to train the network in the succession of the execution of Caffe to reduce limitations and make use of the GPU memory, such that a large number of training sets samples regulate the update in the current optimization step [8].

Reference models

For evaluation, the original U-Net, wide U-Net architecture were used. U-Net is chosen because it is a common baseline for image segmentation. Table 1 presents some performance metrics obtained by different U-Net-based architectures.

Table1. Segmentation results (IoU: %) for U-Net, wide U-Net and architecture UNet++ with and without deep supervision (DS) [7]

		Data sets			
Architecture	**Parameters**	--			
		cell nuclei	**colon polyp**	**liver**	**lung nodule**
U-Net	7.76M	90.77	30.08	76.62	71.47
Wide U-Net	9.13M	90.92	30.14	76.58	73.38
UNet++ w/o DS	9.04M	**92.63**	**33.45**	79.70	76.44
UNet++ w/ DS	9.04M	92.52	32.12	**82.90**	**77.21**

Figure 1 shows the input images and outcomes generated by the mentioned solutions [7].

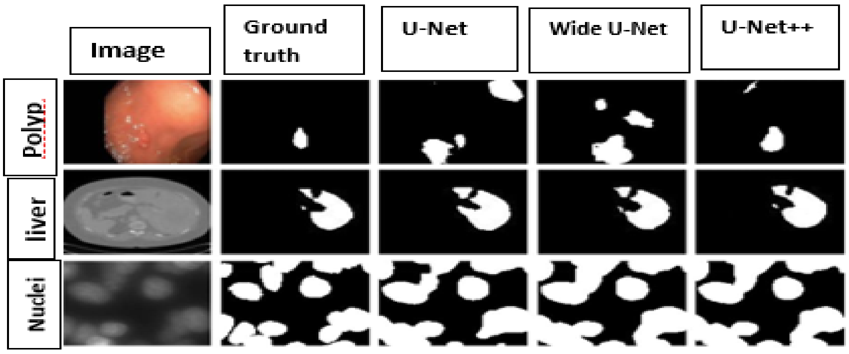

Fig. 1. A comparison between U-Net, wide U-Net, and U-Net++, showing segmentation results for polyp, liver, and cell nuclei datasets

Conclusion

Due to the importance of more accuracy in medical image segmentation, UNet++ was introduced. The proposed architecture takes the benefit of re-designed skip pathways and deep supervision. The re-designed skip pathways aim at minimizing the semantic gap between the feature maps of the encoder and decoder subnetworks, resulting in a possibly much easier optimization problem for the optimizer to take care of and solve [2]. UNet++ was evaluated using different medical imaging. The experiments established that UNet++ with deep supervision achieved an average IoU gain point over U-Net and wide U-Net, to address the need for more accuracy in medical image segmentation, it has the benefit of re-designed skip pathways and simpler optimization.

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